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Modeling Economic Behavior and Market Optimization by Integrating Game Theory and Deep Generative Models

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Abstract The regular characteristics of economic behavior are important considerations for the optimization strategy of market development. In this paper, based on Agent's Modeling and Simulation (ABM) methodology technique, a physical model of macroeconomic system is established in the context of China's economy, and mathematical economic methods are integrated to propose a model for the evolution of China's macroeconomic system. Subsequently, the single leader single follower Stackelberg game theory is used as the theoretical framework, and the multi-leader single follower Nash-Stackelberg game theory is further proposed to analyze the occurrence mechanism of economic behavior. By applying this analytical method to the optimization of the market revenue allocation of the wind power merchant alliance, the overall revenue of the wind power merchant is improved compared with that of the pumped storage unit before joining the alliance, and the revenue of pumped storage is as high as 8.54 times of that of the original one. It shows that the analytical model designed in this paper can effectively leverage the multi-leader single-follower Nash-Stackelberg game theory to realize the win-win situation in the market strategy.

Index Terms macroeconomic system evolution, Stackelberg game theory, ABM method, economic behavior

I. Introduction

Subject behavior is an indispensable part of the economic field, especially the market economy. Generally speaking, the emergence of abnormal phenomena in market economy is not as untraceable as it seems on the surface, in fact, the complexity of the behavior of micro subjects is the fundamental reason that induces the occurrence of abnormal phenomena in the economy [1]-[3]. Therefore, the behavior of micro subjects can be taken as the fundamental starting point, in-depth analysis of the real key behavioral characteristics, and then propose and construct an economic model suitable for analyzing the behavior of micro subjects [4]-[6]. Seeking the consistent conditions of individual rationality and collective rationality, exploring the relationship between economic operation and the behavior of the subject, opening the behavioral black box, relaxing the classical assumptions, so as to explore the effective way to solve the complex economy.

The current research in economics and management is based on the rational man assumption that individuals follow the principle of self-interest and pursue the maximization of personal interests [7]. However, irrational economic behavior is equally prevalent in real economic activities [8]. For example, altruism is contrary to the assumption of rational man, and when making economic decisions, the decision maker does not maximize his own interests, but chooses to reduce his own benefits [9], [10]. Since the current market regulation and management approach is often based on the rational man assumption, it is necessary to explore the game logic behind economic behaviors and the impact of actors' strategic choices in order to avoid the loss of collective interests that may be brought about by maximizing individual interests, thus reducing the management costs of implementing regulatory measures [11]-[14].

This paper firstly elaborates the feedback mechanism between subject behavior and economic phenomena in the ABM method, as well as the operation process of ABM based on subject behavior. Secondly, with the support of ABM methodology and technology, we design a macroeconomic system logic model and a macroeconomic system model, build an evolutionary model of China's macroeconomic system and describe its mathematical model expression. Then, we explain the theory of single-leader-single-follower Stackelberg game, which leads to the theory and modeling process of multi-leader-single-follower Nash-Stackelberg game, and set up the modeling and analysis model of economic behavior. Finally, the simulation experiment of updating strategy algorithm selection is used to test the validity of the designed analytical model, and the operational optimization effect of the wind power merchant alliance is analyzed to verify the feasibility of the designed analytical model.

II. Modeling and Analytical Models of Economic Behavior

II. A.Analysis of Subject Behavior in ABM

ABM modeling based on subject behavior is to reflect the understanding of subject behavior into the model, in which the interrelationships between subject behavior, between subject behaviors, and between subject behaviors and economic phenomena are systematically and intuitively portrayed. The model is to have two characteristics: first, the model system is to contain numerous interacting subjects. Secondly, the model should have the characteristic of suddenness and be able to dynamically analyze the contingencies caused by the heterogeneity of subject behaviors. On the basis of the ABM model, which is mainly characterized by interactivity, deepening the behavioral analysis and solving the problem of endogenous parameterization of the subject's behavior, it is possible to build a model that reflects the complexity of the economy and is close to the real economy and society.

The impact of subject behavior on the economy is shown in Figure 1.The feedback mechanism between subject behavior and economic phenomena plays an important role in the evolution of the economy, and the degree of the parameterization of the endogenous heterogeneity and interactivity of subject behavior determines the explanatory and adaptive ability of economic theories to the real economy. The so-called endogenous parameterization of behavior is to regard the subject's behavior as an endogenous variable, and dynamically reflect the subject's behavior as well as the interaction between the subject and the environment through the parameterization of the subject's behavior, so as to change the practice of viewing the behavioral attributes as exogenous constants in the traditional economic research. Due to the incomplete information in the real world and the endowment differences in the subject's ability to process information, the results of the subject's processing of information are heterogeneous, resulting in the subject's behavioral performance being heterogeneous and endogenous. Turning the research perspective of economics to the analysis based on human behavior, how to describe the heterogeneous behavioral attributes, how to portray the key behavioral features and critical change states, and how to parameterize the endogenous behaviors are the difficulties of subject-based modeling, and the breakthroughs of combining the model with the economic reality, which can be used to analyze and solve the actual economic problems.

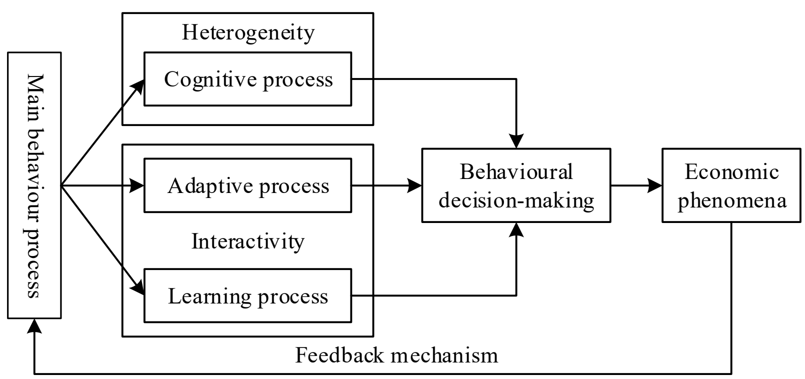

Figure 1: The influence of the main body's behavior on the economy

The processing of endogenous parameterization of the subject's behavior can be done in a hierarchical manner. First, a behavioral classifier is set for the initial behavior of the subject, and a response parameter is set for each behavioral classifier. Of course, subjects within the same behavioral classifier are also heterogeneous and their behavioral performance is different, so the value of the parameter should be different for different subjects. Secondly, considering the interaction between subjects and the subject's ability to learn, action sets and action paths are set, and the subject can re-select the behavioral classifier to which he belongs after interacting with other subjects or after learning in a dynamic way according to the rules. Each behavioral choice of the subject eventually forms a decision set, which in turn examines how individual quantities generate aggregates under different circumstances and how micro-individual behavioral choices affect macroeconomic phenomena. The basic flow of its modeling is shown in Figure 2.

Thanks to the availability of a large amount of micro-behavioral data in the era of big data and high-performance computing technology, the modeling calculation based on the subject's behavior dynamically reflects the heterogeneity and endogeneity of the subject's behavior, and the model's ability to explain the reality is getting stronger and stronger with the increase in the reasonableness of the parameters and the increasing amount of data.

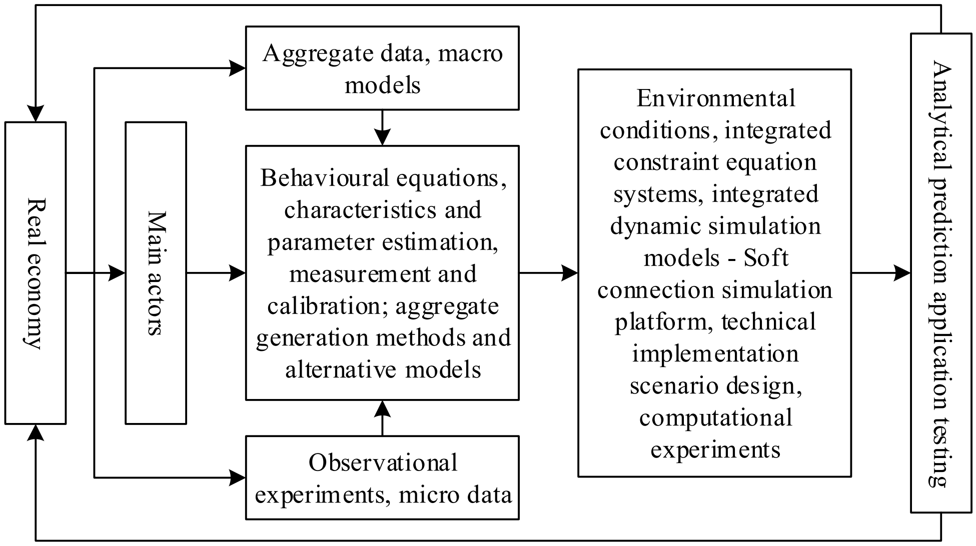

Figure 2: ABM process based on the behavior of the subject

II. B.Modeling the evolution of the macroeconomic system

Taking China as the research object, using the above method to establish a macroeconomic system evolution model, let the GNP be divided into three parts, i.e., equation (1):

$$Y = C + I + G \tag{1}$$

where C is consumption, I is fixed capital investment, and G is government expenditure. Consider that GNP is composed of three components, namely the sum of the production values of the primary, secondary and tertiary sectors. From this, a logistic model of the macroeconomic system can be built, which is a closed-loop system as it omits economic exchanges with foreign countries and only considers the evolution of the country itself. Output is obtained from fixed capital inputs through production transformations, which are part of GNP (the other part is consumption). There is also capital depreciation for each investment, so again there are small feedback loops. Let each investment be a part of GNP, which is determined by the scaling factor σ_i, and thus, the physical model of the macroeconomic system is established.

Based on the physical model and mathematical economic methods can be established as a mathematical model of the macroeconomic system as equation (2)-(3):

$$\begin{aligned}
&0 \le \sigma_0 \le 1,\, 0 \le \sigma_1 \le 1,\, 0 \le \sigma_2 \le 10 \le \sigma_3 \le 1,\, 0 \le \sigma_4 \le 1,\, 0 \le \sigma_5 \le 1 \\
&\frac{dx_1}{dt} = I_1 - \delta_1 x_1,\, \frac{dx_2}{dt} = I_2 - \delta_2 x_2 \\
&\frac{dx_3}{dt} = I_3 - \delta_3 x_3,\, \frac{dx_4}{dt} = I_4 - \delta_4 x_4 \\
&\frac{dx_5}{dt} = I_5 - \delta_5 x_5,\, \frac{dx_6}{dt} = G - \delta_6 x_6 \\
&Y = Y_1 + Y_2 + Y_3,\, Y_1 = e^{\lambda_1 t} \cdot x_1^{\alpha} \cdot la_1^{\beta} \\
&Y_2 = e^{\lambda_2 t} \cdot x_2^{\alpha} \cdot la_2^{\beta},\, Y_3 = e^{\lambda_3 t} \cdot x_3^{\alpha} \cdot la_3^{\beta}
\end{aligned} \tag{2}$$

$$\begin{aligned}
&C = Y\sigma_0,\, I_1 = Y(1-\sigma_0)\sigma_1, \\
&I_2 = Y(1-\sigma_0)\sigma_2,\, I_3 = Y(1-\sigma_0)\sigma_3, \\
&I_4 = Y(1-\sigma_0)\sigma_4,\, I_5 = Y(1-\sigma_0)\sigma_5, \\
&G = Y(1-\sigma_0)(1-\sigma_1-\sigma_2-\sigma_3-\sigma_4-\sigma_5)
\end{aligned} \tag{3}$$

Among them, I_1 is the production investment in the primary industry, I_2 is the production investment in the secondary industry, I_3 is the production investment in the tertiary industry, I_4 is the investment in environmental protection (pollution control), I_5 is other investment, G is government expenditure, x_1 is the production fixed capital of the primary industry, x_2 is the production fixed capital of the secondary industry, x_3 is the production fixed capital of the tertiary industry, x_4 is the fixed capital of environmental protection (pollution control), and x_5 is other fixed assets , x_6 is the fixed capital of the government, $\delta_1,\delta_2,\delta_3,\delta_4,\delta_5,\delta_6$ are the depreciation of each fixed capital, and the proportional factor is $\sigma_0,\sigma_1,\sigma_2,\sigma_3,\sigma_4,\sigma_5$ to determine the part of each investment in GNP, Y_1 is the production function of the primary industry, Y_2 is the production function of the secondary industry, Y_3 is the production function of the tertiary industry, la_1,la_2,la_3 is the input labor force, and $e^{\lambda_1 t},e^{\lambda_2 t},e^{\lambda_3 t}$ is scientific and technological progress.

II. C.Stackelberg's Game Theory Foundations and Extensions

The multi-leader single-follower Nash-Stackelberg game is a kind of promotion in the standard Stackelberg game, therefore, before introducing the multi-leader single-follower Nash-Stackelberg game, the relevant concepts of Stackelberg game are introduced first.

Stackelberg game is a two-stage hierarchical game in the non-cooperative game, the decision-making subjects involved in the game are divided into leaders and followers, in which the leaders act before the followers, maximizing their benefits or minimizing their costs by choosing appropriate strategies. The followers, after the leader's action, act according to the decision made by the leader, and choose the appropriate strategy to maximize their own benefits or minimize the cost. The leader keeps the strategy of the followers unchanged during the optimization of its own strategy, and the followers keep the strategy of the leader unchanged during the optimization of its own strategy, taking turns to optimize its own strategy until it reaches equilibrium and stops optimizing.

The single leader single follower game is the simplest type of Stackelberg game, i.e., there is only one leader and one follower in the game. In mathematical form, Stackelberg game is usually described by a two-layer optimization model, in which the leader's decision-making problem is in the upper layer of the two-layer optimization model, and the follower's decision-making problem is in the lower layer of the two-layer optimization model. The mathematical expression of the single leader single follower game is shown in Eqs. (4)-(9):

$$\min_x F(x,y^*) \tag{4}$$

$$s.t.\ G(x,y^*)=0 \tag{5}$$

$$H(x,y^*)\geq 0 \tag{6}$$

$$y^*\in \arg\min f(x,y) \tag{7}$$

$$g(x,y)=0 \tag{8}$$

$$h(x,y)\geq 0 \tag{9}$$

where, equation (4) is the objective function of the upper level leader problem. Eq. (5) and Eq. (6) denote the equality constraints and inequality constraints of the upper level leader problem, respectively. Equation (7) indicates that the optimal solution y^* is obtained by solving the lower level problem. Eqs. (8) and (9) denote the equational constraints and inequality constraints of the lower level follower problem, respectively. x is the decision vector of the upper level leader problem. y is the decision vector for the lower level follower problem.

The existence and uniqueness of the equilibrium point of the Stackelberg game model is difficult to prove because of its strong nonlinearity and nonconvexity in mathematics. From the mathematical form of the single leader single follower game, it can be seen that even the simplest Stackelberg game model is modeled as a two-layer optimization model, and the two-layer optimization problem is usually NP-hard mathematically, i.e., it is not possible to find an analytical solution to the problem by polynomial methods. Therefore, other methods are needed to solve the Stackelberg game model. Currently, there are three types of classical solution methods to solve this model, namely, two-layer alternating solutions, heuristic methods, and mathematical programming with equilibrium constraints (MPEC) methods.

The MPEC method is usually used to solve the Stackelberg game problem when the lower level follower's problem is a convex optimization problem. Because the satisfaction of the KKT condition at this time is a sufficiently necessary condition for the lower-layer problem to obtain an optimal solution, the lower-layer problem can be KKT reconstructed to transform the two-layer optimization problem into a single-layer optimization problem, and the KKT condition of the lower-layer problem is shown in Eqs. (10)-(12):

$$\nabla_y f(x,y) - \nabla_y g(x,y)\lambda - \nabla_y h(x,y)\gamma = 0 \tag{10}$$

$$g(x,y) = 0 \tag{11}$$

$$0 \le h(x,y) \perp \gamma \ge 0 \tag{12}$$

where λ is the Lagrange multiplier vector corresponding to the equality constraint equation (8). γ is the Lagrange multiplier vector corresponding to the inequality constraint equation (9).

After applying the KKT condition to the reconstruction of the lower problem, the nonlinear complementary constraints shown in Eq. (12) are introduced in the constraints, which do not facilitate the direct solution. Here, the nonlinear complementary constraints generated after the KKT reconstruction are eliminated by employing the large M method with the expressions in Eqs. (13)-(14):

$$0 \le h(x,y) \le M\xi \tag{13}$$

$$0 \le \gamma \le M(1-\xi) \tag{14}$$

where M is a sufficiently large positive number. $\xi \in \{0,1\}$ is an introduced auxiliary logistic variable. It should be noted that when the large M method is used to eliminate the nonlinear complementary constraints, the value of M needs to be chosen reasonably, and when the value of M is too large it may increase the computational burden and make the solving efficiency lower. When the value of M is too small, the complementary constraints will not be satisfied. Therefore, in the actual solution process, a larger value of M is usually taken first to ensure that the complementary constraints are satisfied, and then the value of M is gradually reduced to improve the solution efficiency under the premise of ensuring that the complementary constraints are satisfied. Up to this point, the two-layer optimization model describing the single-leader-single-follower game is finally transformed into a single-layer mixed-integer linear programming problem, whose mathematical expressions are shown in Eqs. (15)-(21):

$$\min_{x,y} F(x,y) \tag{15}$$

$$s.t.\ G(x,y) = 0 \tag{16}$$

$$H(x,y) \ge 0 \tag{17}$$

$$\nabla_y f(x,y) - \nabla_y g(x,y)\lambda - \nabla_y h(x,y)\gamma = 0 \tag{18}$$

$$g(x,y) = 0 \tag{19}$$

$$0 \le h(x,y) \le M\xi \tag{20}$$

$$0 \le \gamma \le M(1-\xi) \tag{21}$$

The multi-leader single-follower Nash-Stackelberg game is a generalization of the single-leader single-follower Stackelberg game, which involves multiple leaders in the upper level of the game model. The multiple leaders in the upper level of the game model are in equal competition with each other, and each leader acts simultaneously to maximize its own benefit or minimize its own cost by optimizing its own strategy, forming a Nash equilibrium. The followers at the lower level of the game model act according to the decisions made by the leaders after the leaders have acted, and choose appropriate strategies to maximize their own benefits or minimize their costs. The leaders keep the strategy of the followers unchanged during the optimization of their own strategy, and the followers keep the strategy of the leaders unchanged during the optimization of their own strategy, taking turns to optimize the strategies of the leaders and the followers until the equilibrium is reached when the optimization is stopped.

III. Tests and Applications of Economic Behavior Analysis Models

III. A. Simulation Experiments for Strategy Algorithm Selection

The specific simulation flow of this section of the simulation experiment is as follows: assume that users choose among 3 transaction types based on their respective transaction selection probabilities (p). Users who choose CoinJoin transactions will form an anonymous set and play a cooperative game, calculate the marginal gain (i.e., the identity value retained by participating in CoinJoin) of all users participating in CoinJoin, and calculate the identity value retained by users choosing shielded transactions and non-shielded transactions. After all users have initiated transactions, simulate the entire process of miners packing transactions, determine whether each user is packed by miners as well as calculate the utility gained by each user from the current round of transactions based on the results of the first game (cooperative game), and finally update the probability of users choosing the three transaction types through the second game (non-cooperative game) and no-regret learning until the optimal transaction strategy is found.

A simulation program is run to emulate the Zcash trading market game involving a number of users and a miner, and the algorithms for updating strategies in the trading market game are compared with a focus on the user type D, and its impact on user actions is analyzed.

In this section, we use the modeling algorithm of this paper (MW) and the $\varepsilon - greedy$ algorithm (EG) as the updating strategy for remorseless learning, respectively, with the following setup parameters: N=80, θ=0.5, B_s =250, s_t =8, s_z =25, *rounds* = 2000. For the model algorithm update strategy in this paper set η =0.15, and for the $\varepsilon - greedy$ algorithm update strategy set ε =0.13. During the game, the trading market fluctuates continuously with the learning of the user and the dynamic change of the trading strategy. Every 10 rounds of the game are counted, and the trend of the selfish miners' packaged trading gains from the trading market is given in Figure 3, and the social welfare of the trading market is given in Figure 4. The trend of miners' packaged gains is a rapid increase in the early stage and shows a smoother fluctuation in the later stage, while the change of the market's social welfare shows a rapid decline in the early stage and a smooth fluctuation in the later stage.

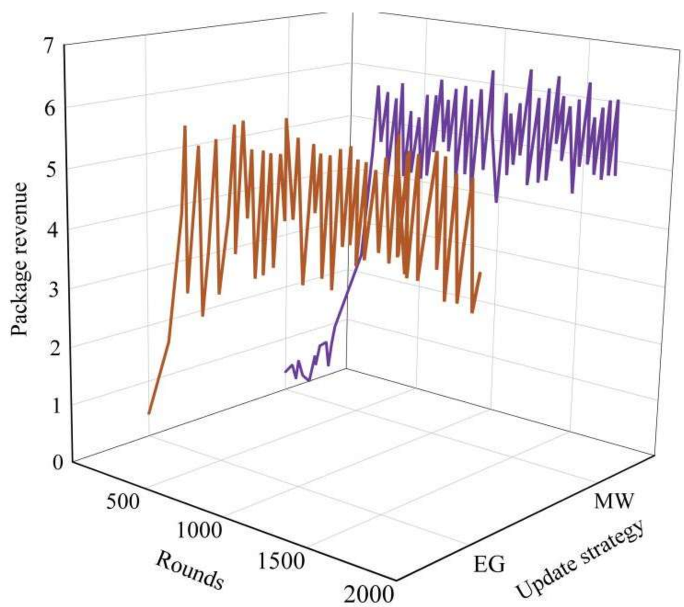

Figure 3: The packaging revenue of miners under the two update strategies

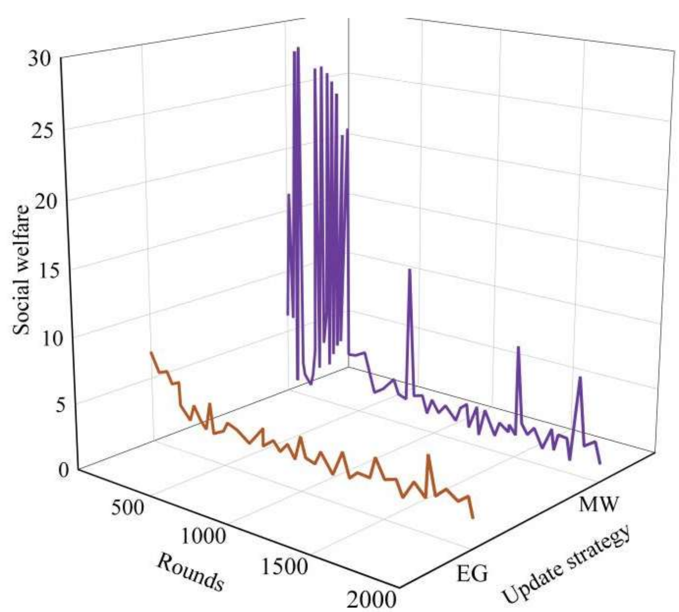

Figure 4: The social welfare of the trading market under two update strategies

For the set of users with identical initial conditions $players$, $\varepsilon - greedy$ algorithmic updating strategy converges faster. In the case of similar total social welfare, the selfish miners under the multiplicative weighting algorithm update strategy have slightly higher packaged returns, a smaller range of fluctuations, and a higher degree of stability. As shown in Fig. 4, in the first 500 rounds, this paper's model algorithm (MW) strategy obviously achieves higher social welfare for the trading market, while after 500 rounds, there is little difference in the overall social welfare of the trading market under the two strategies.

By analyzing the utility obtained by each user throughout the game, it is found that the user's utility is overall higher under the model algorithm (MW) strategy of this paper. The utility of user number 5 under the two strategies is shown in Fig. 5, and the utility of this user is counted with the modeling algorithm of this paper (MW) and the $\varepsilon - greedy$ algorithm (EG) as the updating strategy, respectively. By analyzing the data of the whole game, it can be concluded that under the update strategy of $\varepsilon - greedy$, this user tends to choose non-blocking transactions, while under the update strategy of this paper's model algorithm (MW), he or she chooses blocking transactions with a selection probability of 99.99%. Combined with Fig. 3, it can be concluded that this paper's modeling algorithm finds a more optimal trading strategy for user number 5.

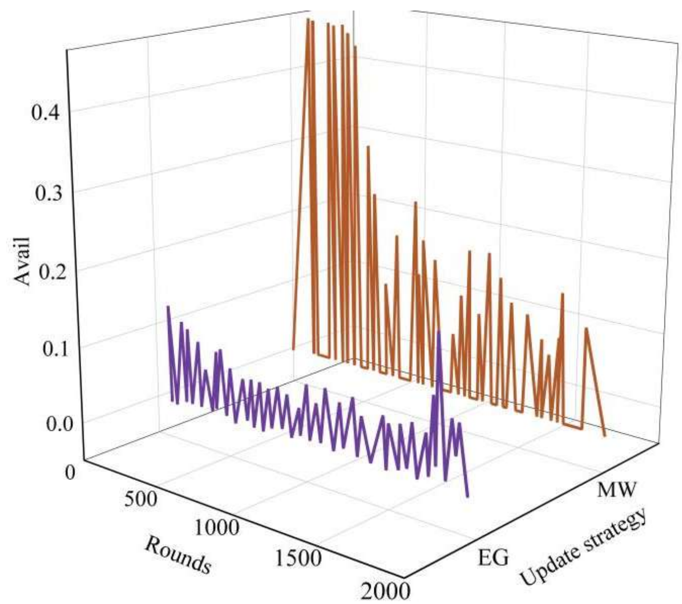

Figure 5: The utility of user number 5 under the two update strategies

III. B. Operational optimization of the wind power merchant alliance

In this section, the wind turbine spot market model currently being tested is selected as the research object, and for the alliance formed by multiple wind farms and pumped storage power stations, the numbering of the three wind turbines is carried out sequentially using W1, W2, and W3. Using the economic behavior modeling and analysis model proposed above, an optimal revenue allocation strategy is designed for the revenue generated from the alliance's overall participation in the spot market among multiple wind farms and pumped storage power plants. Next, the analysis of the optimal return scenarios of the market players under this allocation strategy is carried out, as well as the effect of the risk preference coefficient.

III. B. 1) Market strategy optimization effects

Table 1 gives the final revenue of each market player obtained from the revenue allocation method based on the analytical model of this paper in different wind power alliance scenarios. Where "√" indicates the members in the alliance. From the final revenue situation in Table 1, it can be seen that after the wind turbine operator and pumped storage power plant jointly participate in the spot market, the overall revenue of the wind turbine operator is improved compared with that before the pumped storage unit joins the market as well as the separate participation in the market, and the revenue shared by pumped storage is as high as 8.54 times of the original one, which indicates that the market optimization strategy based on the game theory and deep learning proposed in this paper has the characteristics of win-win situation for all parties.

Table 1: Expected revenue in different coalitions

Alliance situation				Expected revenue situation (10^3\$)			
W1	W2	W3	Pumped storage	W1	W2	W3	Pumped storage
—	√	√	—	—	82.45	8.60	—
√	—	—	√	72.35	—	—	5.26
—	—	√	—	—	—	84.56	—
√	—	√	—	73.56	—	75.12	—
—	—	—	√	—	—	—	5.87
√	—	√	—	81.6	—	90.01	—
√	√	—	—	83.8	76.4	—	—
√	√	√	√	78.9	81.6	76.6	8.54

III. B. 2) Impact of Risk Appetite Coefficients on Operational Strategies

In order to compare the impact of different risk preference coefficient settings on the coalition's operational strategies and returns, Figure 6 presents the overall expected coalition returns and the CVaR efficient frontier with different risk preference coefficients.

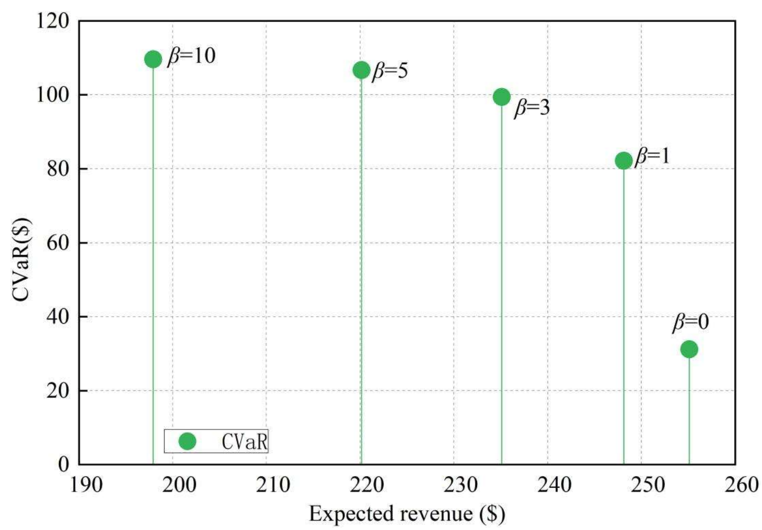

Figure 6: Efficient frontier of CVaR vs expected revenue

It can be seen that as the risk appetite coefficient increases, the total expected return of the coalition is gradually less and the CVaR gradually increases, and when the risk appetite coefficient is small, the total expected return of the coalition decreases slowly with the increase of CVaR. However, when the risk appetite coefficient is large, even a small increase in CVaR will still result in a significant decrease in the total expected return of the coalition.

IV. Conclusion

This paper adopts the ABM methodology to model and analyze the economic behavior of market trading subjects, uses the macroeconomic system evolution model to explore the current macroeconomic development trends and laws, and uses the multi-leader single-follower Nash-Stackelberg game theory to guide the distribution of interests of multi-party subjects in the market transaction, and puts forward the modeling and analytical model of economic behavior. In the simulation experiment of algorithmic choice of CoinJoin trading, the user utility under the algorithm of this paper's model is higher in general and pushes the users to choose blocking trading with 99.99% selection probability. In the market operation optimization strategy of the wind turbine alliance, the model proposed in this paper assists the wind turbine operators to increase the overall revenue compared to the pre-pumped storage units and the revenue shared by pumped storage is up to 8.54 times of the original revenue.

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